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Souza, Alessandra S ; Oberauer, Klaus

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BRIEF REPORT

Time-based forgetting in visual working memory reflects temporal distinctiveness, not decay

Alessandra S. Souza · Klaus Oberauer

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Abstract Is forgetting from working memory (WM) better explained by decay or interference? The answer to this question is the topic of an ongoing debate. Recently, a number of studies showed that performance in tests of visual WM declines with an increasing unfilled retention interval. This finding was interpreted as revealing decay. Alternatively, it can be explained by interference theories as an effect of temporal distinctiveness. According to decay theories, forgetting depends on the absolute time elapsed since the event to be retrieved. In contrast, temporal distinctiveness theories predict that memory depends on relative time, that is, the time since the to-be-retrieved event relative to the time since other, potentially interfering events. In the present study, we contrasted the effects of absolute time and relative time on forgetting from visual WM, using a continuous color recall task. To this end, we varied the retention interval and the inter-trial interval. The error in reporting the target color was a function of the ratio of the retention interval to the inter-trial interval, as predicted by temporal distinctiveness theories. Mixture modeling revealed that lower temporal distinctiveness produced a lower probability of reporting the target, but no changes in its precision in memory. These data challenge the role of decay in accounting for performance in tests of visual WM, and show that the relative spacing of events in time determines the degree of interference.

Keywords Visual working memory · Forgetting · Decay · Temporal distinctiveness

A. S. Souza · K. Oberauer
Department of Psychology, University of Zurich, Zurich, Switzerland

A. S. Souza (✉)
Department of Psychology, Cognitive Psychology Unit, University of Zürich, Binzmühlestrasse 14/22, 8050 Zurich, Switzerland
e-mail: a.souza@psychologie.uzh.ch

Introduction

Most tasks require the maintenance of bits of information in mind over a brief interval. For example, imagine you go shopping with a friend. You stop at the large display cabinet of a bijouterie shop in the search for an interesting pair of earrings. When you have found a perfect pair, your friend calls your attention to the approach of an acquaintance. You turn away from the cabinet to greet your friend, but when you turn back to it, you realize you can no longer tell where the earrings you were interested in are. This quotidian example illustrates what happens when we lose the information stored in a system known as working memory (WM).

The cause of forgetting from WM is the subject of an ongoing debate. On the one side there are WM theories assuming that the loss of information is due to time-based decay: memory traces fade away over time (Barrouillet & Camos, 2012; Burgess & Hitch, 2006; Cowan, 2001). The opposing view proposes that forgetting is due to interference: Representations of different events overlap with each other to the degree that the events are similar to each other, and occur in close temporal proximity. This overlap impairs one's ability to properly recall the relevant information (Brown, Neath, & Chater, 2007; Lewandowsky & Farrell, 2008; Nairne, 1990; Oberauer, Lewandowsky, Farrell, Jarrold, & Greaves, 2012).

To distinguish between decay and interference, it is necessary to determine whether memory fades simply as time passes, or whether memory is impaired by the occurrence of events unfolding over time. A very strong case against time-based decay has been made in studies of verbal WM (Berman, Jonides, & Lewis, 2009; Jalbert, Neath, Bireta, & Surprenant, 2011; Lewandowsky, Geiger, Morrell, & Oberauer, 2010; Nairne, 2002; Oberauer & Lewandowsky, 2008, 2013; White, 2012). This research showed that the sole passage of time cannot explain forgetting when verbal material is tested. A different picture has emerged in studies investigating forgetting from visual WM. Across several experiments, Ricker and Cowan (2010, 2014) observed that recognition of hard to verbalize characters decreased as the length of an unfilled retention interval increased. Woodman, Vogel, and Luck (2012) and C. C. Morey and Bieler (2013) also observed worse recognition performance for visual objects when the retention interval was increased. Likewise, in the studies by Pertzov, Bays, Joseph, and Husain (2013) and Zhang and Luck (2009), in which a continuous recall task was used, the error in reporting the relevant feature of a target increased as a function of an unfilled retention interval. Zhang and Luck (2009) also submitted their data to mixture modeling to estimate two memory parameters: the probability that the target item was accessible at the time of test, and its precision in memory. Forgetting was reflected in a lower probability of recalling the target, but not in its precision.

Overall, these findings show that visual WM declines over time. One possible explanation of these findings is that memory representations decayed. An alternative explanation in terms of interference rests on the assumption that time serves as a retrieval cue for a given event, and that representations of events overlap and interfere with each other as a function of their temporal distinctiveness, that is, their separation from other events on the psychological timeline. This is the core idea put forward by temporal distinctiveness theories such as SIMPLE (Brown et al., 2007). According to distinctiveness theories, the psychological representation of time is logarithmically compressed, such that temporal distances between events shrink as they recede into the past. As a consequence, the distinctiveness of a target event relative to other events in time is a function of the relative time since the events. Specifically, distinctiveness is indexed by the ratio between two time intervals: The elapsed time since presentation of the target information (e.g., the current memory array), and the elapsed time since the occurrence of some other, potentially interfering earlier event (e.g., the memory array or the test display in the previous trial). This ratio reflects the distinctiveness in memory of the target of recall in comparison to another potential candidate for retrieval. The higher the ratio, the more similar the target is to this other event, and the worse performance gets.

The role of temporal distinctiveness in producing time-based forgetting in visual WM is illustrated by the results of Shipstead and Engle (2013). They used a color change detection task: participants compared a test array with a memory array to determine whether one of the objects has changed. Shipstead and Engle varied both the retention interval (RI) and the inter-trial interval (ITI). In this way, they changed the relative spacing of the trials in psychological time, and consequently their distinctiveness. For example, increasing the RI, while holding the ITI constant, makes the memory array in the current trial recede further into the past. As a consequence of the logarithmic compression of psychological time, increasing the RI compresses the interval between the current trial's memory array and the preceding trial's test array, thereby increasing the confusability of these events when the RI is long compared to when it is short. Notably, temporal distinctiveness and decay theories make the same prediction for this contrast: memory becomes worse with a longer RI. Where the two theories differ is with regard to the role of the ITI: when the ITI is increased while holding the RI constant, distinctiveness theories assume that temporal distinctiveness between subsequent trials increases, and better memory is predicted. The decay hypothesis, in contrast, predicts no effect of ITI.

In sum, according to temporal distinctiveness theories, memory depends only on the ratio of RI to ITI, whereas according to decay theories, memory declines with increasing absolute RI, even when the ratio of RI to ITI is held constant. Accordingly, Shipstead and Engle (2013) showed that performance in the change-detection task was a function of the relative time between trials (main effects of both ITI and RI), and not of the absolute RI within a trial. This finding shows that events that crowd in a certain region of the psychological timeline tend to interfere with each other, leading to worse memory.

In the present study, we contrasted the impact of absolute time and relative time in producing forgetting from visual WM using a continuous color recall task (Prinzmetal, Amiri, Allen, & Edwards, 1998; Wilken & Ma, 2004; Zhang & Luck, 2008). This task requires the memorization of colored patches over a brief interval, and the recall of the color of one target item by means of a continuous color wheel. We examined whether the error in reporting the target's color was a function of the length of the RI alone, as predicted by decay theories, or of both the RI and the ITI, as predicted by temporal distinctiveness theories. For a particularly incisive test for any contribution of decay to forgetting, we created conditions with short and long RIs that had the same temporal distinctiveness. If time-based forgetting is entirely due to temporal distinctiveness, there should be no difference in memory between these conditions. In contrast, if decay contributes to memory, perhaps in addition to distinctiveness, the long-RI condition should lead to more forgetting when distinctiveness is held constant.

The continuous recall task allows the estimation of several parameters related to the maintenance of representations in WM, such as the probability that the target item is accessible at the time of test, and the precision with which the target item is remembered (cf. Bays, Catalao, & Husain, 2009; Zhang & Luck, 2008). Time-based forgetting could affect these parameters differentially. To the best of our knowledge, no study has investigated how these parameters change when both the RI and the ITI are manipulated.

Method

Participants

Thirty-six students (31 women; mean age=23.6 years) from the University of Zurich took part in one 1-h session in exchange of course credits or 15 Swiss francs. Participants read and signed an informed consent form prior to the study, and were debriefed at the end.

Materials and procedure

The experiment was programmed using MATLAB and the Psychophysics Toolbox extension (Brainard, 1997; Pelli, 1997).

Each trial began with the presentation of a white fixation cross (see Fig. 1). Participants were instructed to start repeating "der-die-das" in a microphone at this point to discourage verbal encoding of the colors. Next, a memory array comprising six colored disks appeared (1,000 ms). The disks were evenly arranged on an imaginary circle centered in the screen. The color of each disk was ramdomly sampled from a color wheel with 360 values evenly distributed on the hue dimension in the HSL (*hue, saturation, and lightness*) color model with saturation=1 and lightness=0.5. Each disk color was at a minimum distance of 20° on the color wheel from the color of the other disks. The offset of the memory array was followed by a blank RI. At the end of the RI, a test display was shown which comprised the color wheel, a white circle outline around the previous location of one colored disk (target), and the mouse pointer in the center of the screen. Participants had to indicate the color of the target by clicking on the color wheel. The target was chosen at random on each trial. After responding, a blank ITI folllowed before the next trial started. Participants were instructed that they could stop articulation during the ITI. Articulations were recorded. Instructions emphasized accuracy, but not speed.

We ortogonally manipulated the duration of the RI and of the ITI. Figure 2 depicts the timing of events in each condition. The ITI durations were selected such that the crossing of the short ITI with the short RI (short–short condition) produced roughly the same temporal distinctiveness as the crossing of the long ITI with the long RI (long–long condition).

To estimate the temporal distinctivenes of the current memory display compared to the one in the previous trial, we computed how much time had elapsed since these events and the current memory test. For the memory array presented in the current trial, this time equals the RI. For the memory array in the previous trial, this value equals 2×RI+ITI+RT, with the RT representing the response time in the previous trial.[1] The ratio between the two values represents the distinctiveness of the current memory array compared to the memory array in the previous trial. The smaller this value, the higher the distictiveness of the current memory array (see Fig. 2).

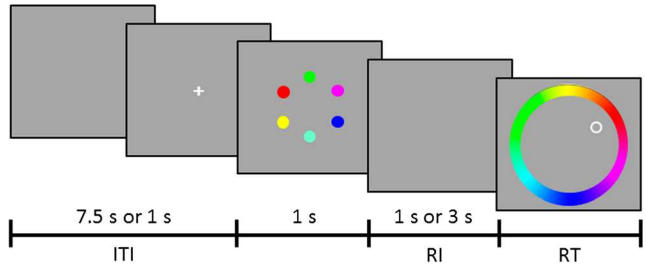

Fig. 1 Flow of events in the experiment. *ITI* inter-trial interval; *RI* retention interval; *RT* reaction time. The ITI includes the blank interval after the response (either 7 or 0.5 s) and the presentation of the fixation cross (0.5 s)

Participants completed one experimental session comprising four blocks of 80 trials. Each block consisted of one of the four experimental conditions. The order of the conditions was counterbalanced across participants using a latin square. In the middle of each block, participants could take a short break.

Data analyses

For each trial, we computed a measure of recall error (i.e., the distance in degrees in the color wheel between the reported color and the target's true color), which can fall between +180° and –180°. These values were used to plot the distribution of responses around the target's color. The absolute value of the recall error was used to compute the mean deviation from the target color in each condition. We applied a probabilistic mixture model (cf. Bays et al., 2009) to these data that estimates three parameters from the error distribution: (1) the probability that the participant guessed in a given trial (*Guessing*); (2) the probability that the participant incorrectly reported one of the non-target items (*Non-target recalls*); and (2) the *precision* with which the target was recalled, given that it was recalled. The probability that the target was recalled was computed as 1 – (*Guessing*+*Non-target recalls*).

The decay hypothesis states that only increases in the RI produce forgetting, whereas the distinctiveness theory holds that memory becomes worse with longer RIs and with shorter ITIs. Importantly, conditions with similar temporal distinctiveness values (i.e., the short–short and long–long conditions) should lead to comparable levels of performance. For the conditions in our experiment, temporal distinctiveness theories predict main effets of RI and ITI, but no interaction (see online supplementary materials).

We submitted our data to a Bayesian ANOVA (BANOVA; Rouder, Morey, Speckman, & Province, 2012).[2] This analysis computes the strength of the evidence for the presence or absence of an effect. The BANOVA essentially compares the likelihood

[1] To estimate the necessary response time (RT) that would roughly equate the distinctiveness of the short and long RIs, we used RT estimations based on our previous experience with tasks in which similar retention intervals were used.

[2] We used the BayesFactor package (v.0.9.5; R. D. Morey & Rouder, 2013) implemented in R. The anovaBF function was used with its default settings ("medium" prior scale for fixed effects, and "nuisance" prior scale for the random effect).

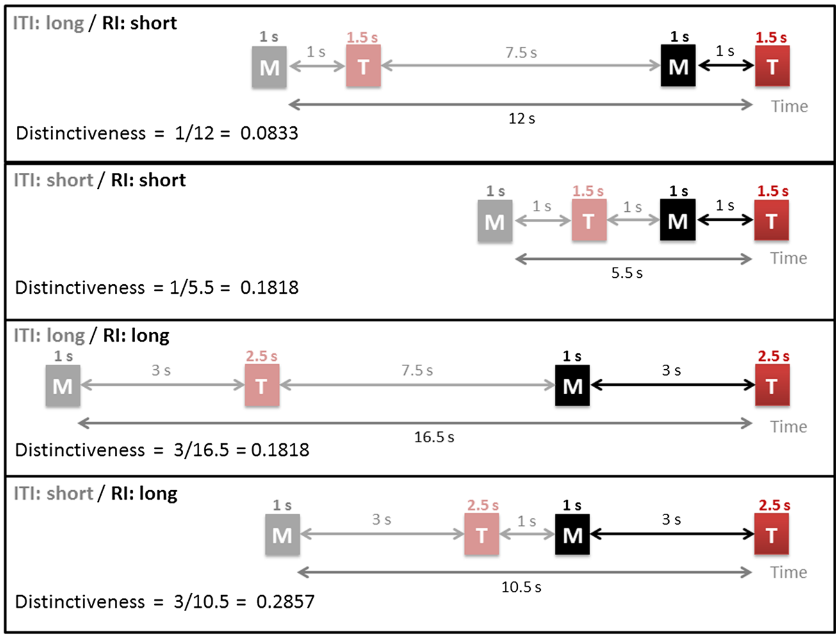

Fig. 2 Timing in each condition. *M* memory display; *T* test display. The duration of each event is printed at the top of it. The temporal distinctiveness of the current memory display (depicted in *black*) is the ratio between the RI and the time elapsed since presentation of the memory display in the previous trial (depicted in *gray*). Lower values indicate higher distinctiveness

of the data given several alternative linear models, including or omitting the main effects and interactions between the variables of interest (fixed effects) while taking into account the effects of nuisance variables (random effects; e.g., participant). It estimates the likelihood of the data in light of one model (e.g., M_0=null hypothesis) in comparison to another model (e.g., M_1=alternative hypothesis). The ratio of these two values is the Bayes factor (BF). The BF should be interpreted as the multiplicative factor by which our ratio of prior beliefs in the two hypotheses should be updated in face of the data. For example, if a model including the effect of ITI is compared to a model without this effect, and the returned BF=10, this means that the data are 10 times more likely under the model assuming an effect of ITI than the model omiting this effect, and our ratio of prior beliefs should be updated by a factor of 10 in favor of this model.

We also submitted our data to a repeated measures ANOVA. The pattern of significant effects was similar to the one obtained for the BANOVA. The ANOVA results are provided in the online supplementary materials.

Results and discussion

Although we did not emphasize speed, analyzing the RT is important to check the accuracy of our estimation of distinctiveness. Table 1 displays the estimated and obtained RT and distinctiveness in each condition. The estimated and obtained values of distinctiveness are similar to each other, and therefore in subsequent analyses, we used the estimated distinctiveness as a predictor.

Figure 3a depicts the distribution of responses around the target's true color. Figure 3b shows the mean deviation in each condition. Response deviations were smallest in the long–short condition and largest in the short–long condition. Response deviations in the short–short and long–long conditions were of intermediate magnitude, and had values very close to each other.

Table 2 presents the results of the BANOVA on the absolute deviation as the outcome variable. In comparison to the null model, the model with both main effects had the highest

Table 1 Estimated and obtained reaction time (*RT*) and distinctiveness values

Condition	Estimated		Obtained		
ITI–RI	RT	Distinctiveness	Mean RT	95 % CIs	Distinctiveness
Long–short	1.5 s	0.0833	2.4 s	(1.8, 3.1)	0.0775
Short–short	1.5 s	0.1818	2.0 s	(1.7, 2.4)	0.1666
Long–long	2.5 s	0.1818	2.7 s	(1.9, 3.4)	0.1796
Short–long	2.5 s	0.2857	2.5 s	(1.9, 3.2)	0.2857

95 % CIs 95 % within-subject confidence intervals; *ITI* inter-trial interval; *RI* retention interval

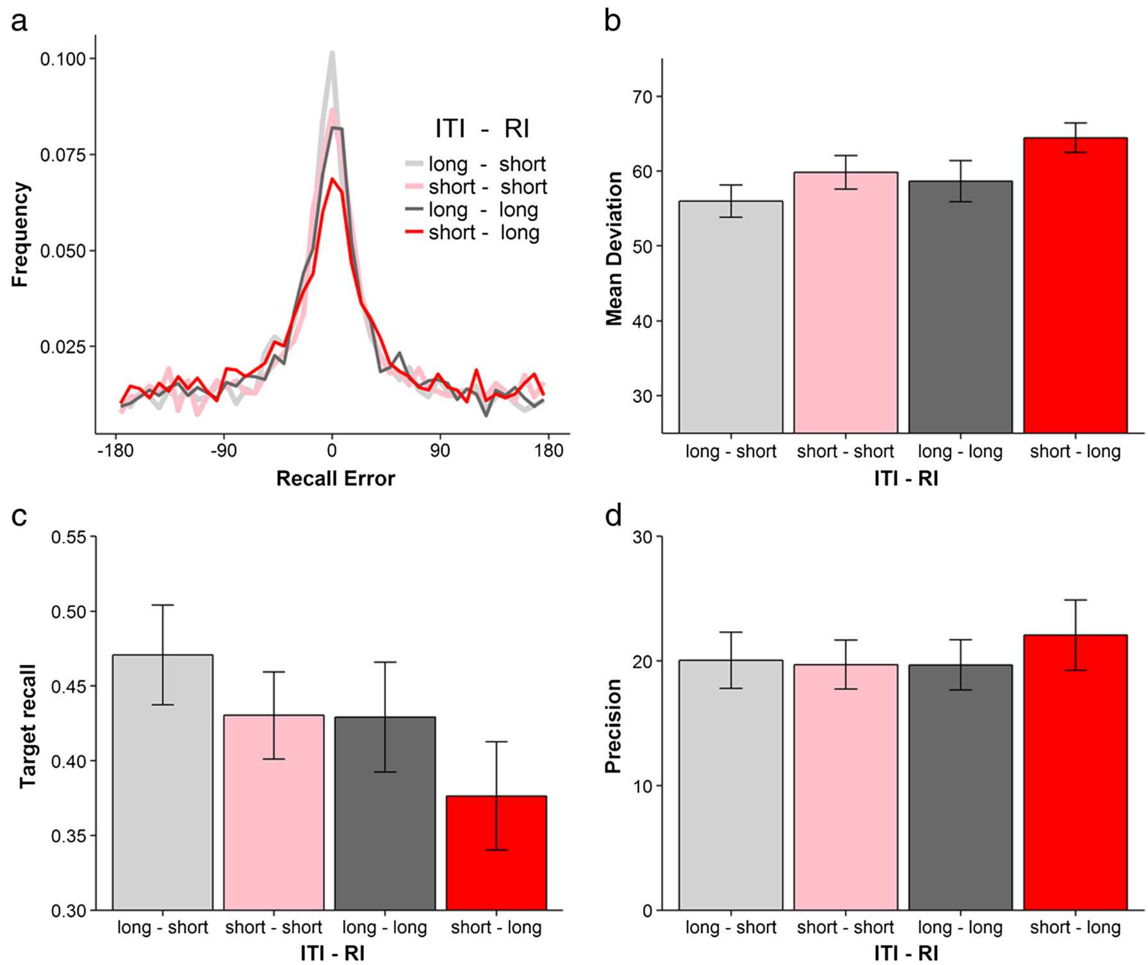

Fig. 3 **a** Frequency of response deviations around the target's true color (in degrees) separately for each condition (ordered from the highest to the lowest distinctiveness). **b** Mean absolute deviation. **c** Probability of recalling the target. **d** Recall precision. *Error bars* 95 % within-subject confidence intervals. *ITI* inter-trial interval; *RI* retention interval

Table 2 Bayes factor (BF) of each tested model

Measure	Linear models			
Comparison	ITI+id	RI+id	ITI+RI+id	ITI+RI+ITI×RI+id
Absolute deviation				
Each model/null	5,080	24.5	124,274	6,189
Best model/each model	24.5	5,083	1	20
Target recall				
Each model /null	3.7	4.4	20.1	5.3
Best model/each model	4.6	5.3	1	3.8
Target precision				
Each model /null	0.25	0.25	0.06	0.03
Best model/each model	4	4	16.66	33.3

For each measure, the first line reports the BF of the model at the top of the column in relation to the null model, and the second line reports the BF of the best model to the model at the top of the column. The best model is the model with the highest BF in comparison to the null model. For target precision the best model was the Null model

ITI inter-trial interval; *RI* retention interval; *id* participant

BF. This model should be preferred over the remaining models by a factor of at least 20 (see row best model/each model in Table 2). As shown in Fig. 3b, conditions with equivalent distinctiveness (i.e., short–short and long–long) produced similar levels of performance despite the different RIs. We compared these two conditions with a Bayesian *t* test, which yielded a BF=0.04 for the alternative model relative to the null model. The reciprocal of this value expresses the strength of evidence for the null model over the alternative model. Therefore, these data are 25 times more likely under the model assuming no differences between these conditions than under a model assuming that the conditions differ. This result provides strong evidence against any contribution of time-based decay to forgetting. Finally, we tested a linear model in which the absolute deviation was predicted by the estimated distinctiveness of the conditions. The BF of this model was of 4.6×10^6 in comparison to the null model.

In sum, the obtained pattern of errors was as predicted by temporal distinctiveness theories: the recall error was a function of the distinctiveness of trials in each condition, with conditions with similar distinctiveness values (short–short and long–long) leading to similar levels of performance.

We submitted the response distributions to mixture modeling, separately for each subject and condition. The means and confidence intervals for each estimated parameter can be found in the online supplementary materials. Our main interest was in analyzing the probability of recalling the target and its precision. Therefore, we are not going to focus on the effects of our manipulations on guessing and non-target recalls, but only on the estimation of target recalls derived from these measures.

Figure 3c, d depicts the two memory parameters related to maintenance of the target item in memory. The probability of recalling the target was affected both by the ITI and the RI, and tracked the distinctiveness of the trials. Precision did not change consistently across conditions. We also ran BANOVAs on these measures (see Table 2). For probability of recall, the model with both main effects had the largest BF, and this model should be preferred over the remaining models by a factor of at least 3.8. We also tested a model in which the probability of recall was predicted from the distinctiveness of the conditions. This model yielded a BF of 28, showing that the likelihood of the data under a model assuming that target recalls were determined by the temporal distinctiveness exceeds by 28:1 the probability of the data under the null model. For the precision of recall, BFs favored the null hypothesis (no effect of either ITI or RI) by a factor of at least 4 over all alternative models.

Conclusion

Our results show time-based forgetting from visual WM. Forgetting, however, was not caused by the absolute time for which representations had to be maintained in WM, as predicted by decay theories, but by the relative spacing of trials, and therefore their distinctiveness from each other on the psychological timeline. These findings challenge previous interpretations of time-based forgetting as reflecting decay of representations in visual WM. In previous studies (e.g., C. C. Morey & Bieler, 2013; Pertzov et al., 2013; Ricker & Cowan, 2010, 2014; Woodman et al., 2012; Zhang & Luck, 2009), the RI was varied while the ITI was held constant. In this case, the same pattern of forgetting would be expected from decay and from distinctiveness theories. The present findings show that, when conditions are created that disentangle the predictions of both theories, temporal distinctiveness better explains the results. This is particularly striking in the comparison of the short–short with the long–long condition: If decay had produced forgetting over and above the effect of temporal distinctiveness, then we should have observed an effect of RI when these conditions were compared, because that comparison keeps temporal distinctiveness constant. Performance in these conditions was similar to each other as predicted by temporal distinctiveness.

Our findings are, therefore, in agreement with interference accounts postulating that time serves as a retrieval cue for a target event, and when events are crowded in time, they are difficult to retrieve (Brown et al., 2007). Our findings replicate and extend the ones reported by Shipstead and Engle (2013) using a different memory paradigm. Moreover, our results suggest that temporal distinctiveness affects the probability of correctly retrieving information from WM, but not its precision in WM, in agreement with the finding of Zhang & Luck (2009) that a longer RI reduces probability of recall, not precision. Whereas those authors interpreted their finding as reflecting "sudden death" of representations in visual WM—a form of decay—our results point to an interference explanation: Low temporal distinctiveness increases the chance of confusing items from the current trial with items from the preceding trial.

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